Optimizing selective laser sintering process by grey relational analysis and soft computing techniques

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Abstract

Selective laser sintering (SLS) is a novel fabrication technique with multiple industrial applications in different industrial sectors. Choosing optimum combination of elements which lead to the best component properties and lower process cost are required in the SLS process. In this study, we focused on advanced modeling and optimization method developed for obtaining the best mechanical properties of SLS produced glass filled polyamide parts. The key processing parameters examined were part bed temperature, laser power, scan speed, scan spacing, and scan length. Response output properties measured were elongation and ultimate tensile strength. Five factors with three levels according to the central composite design were trailed. Adaptive neuro-fuzzy inference system (ANFIS) was employed to generate a mapping relationship between the process factors and the experimentally observed responses. In order to achieve best mechanical characteristics, the acquired model was used by simulated annealing algorithm as an objective function. Grey relational analysis (GRA) as a multi-response optimization technique was also applied to evaluate which modelling technique could perform best for defining the process elements to obtain the highest mechanical properties. In comparing the two optimization methods, the results indicated that the ANFIS-SA system outperformed the GRA in finding optimal solutions for the SLS process applied for glass fiber reinforced part production.

Keywords: Selective laser sintering; Adaptive neuro-fuzzy inference system; simulated annealing algorithm; grey relational analysis

1. Introduction

The selective laser sintering (SLS) was invented in 1989 [1]. In this process, laser employed to melt polymer powders. In order to reduce the thermal distortion, metal powder bed should be melted to below the melting point of the material and at the same time assist melted fusion to the prior layer. After that, each layer is fused by laser for sintering the material. The melted powder shapes the parts and the section which is un-sintered, makes main structure of the parts. The SLS can be classified as a complicated process, as many fabricated elements must be controlled, see process schematic in Fig1.

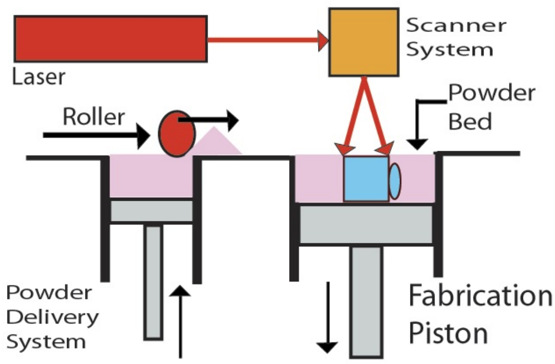

Fig 1. A structure of SLS process

In the case of development of empirical models, some statistical techniques and mathematical modeling such as Response Surface Methodology (RSM) has been used to correlate relationship between SLS process inputs and its main outputs. Bacchewar et al. [2] developed a new mathematical model to determine the effect of input factors on the polymer product made by SLS. They used a CCD (central composite design) as the strategy of experimental work. They found within their design of experiments that hatch distance was the most important parameter in terms of resulting mechanical properties. Sharma et al. [3] with using of dynamic mechanical analyzer, investigated the of laser sintered produced samples. They found that with increasing some input elements like scan length, part bed temperature and laser power the storage modulus also increased; and that it was decreased with increasing scan spacing. Furthermore, they found that scan spacing was the most prominent factor amongst all parameters investigated. Design of experimental methodology is a popular method for optimization of process parameters, particularly for complex laser based processes for which it is difficult to develop fundamental model for [4,5].

Dingal et al. [6] used a design of experiment strategy with seven elements including laser pulse on-time, laser peak power, and interval-between pulses, and responses including density, porosity and hardness. The results show that the laser peak power density had the highest impact on the laser sintering process. Design of experiments methodology has also been applied for metal Selective Laser Melting (SLM) in addition to Selective Laser Sintering [7]. Negi et al. in order to improve service life in glass-filled polyamide in SLS process, studied the impact of process factors including part bed temperature and beam speed on the dynamic mechanical properties [8]. The CCD of experiments was applied for their systematic experiment methodology. From the results it can be observed that with reducing bed temperature, dynamic mechanical characteristics were reduced [9]. The ANOVA results from this work indicated that the scan spacing and laser power had a high level of impact on the surface roughness and that for minimizing of surface roughness, the bed temperature should be set to the lower level. The influence of some input parameters on the tensile strength, elongation and yield strength of glass filled polyamide parts produced by the SLS process was examined [10]. A CCD was implemented in this work as the design of experiments with the response equations derived from the experimental results. The results from this work indicate that the scan spacing and scan speed were the most important parameters in terms of effecting the mechanical property outputs. The effect of same input parameters on the flexural strength of the samples was also examined.

Negi et al. [11] applied both RSM and ANN for the prediction of shrinkage in laser SLS sintered glass fiber reinforced polymer (PA 3200GF) samples. The RSM and ANN models were compared for their ability to predict shrinkage. Results indicated that ANN was better than RSM in both data fitting and estimation abilities. Munguia et al. [12] in order to predict build time in SLS process used an ANN with part height, volume, and bounding box considered for input parameters. The results from this work indicated good potential for the ANN-based approach to be employed for the SLS process. Boillat et al. [13] used ANN in order to optimize the SLS process for a component of circular geometry and also applied an ANFIS model which typically has lower error levels in compression ANN. Shen et al. [14] applied ANN to predict the density of SLS samples. The inputs of this ANN were laser power, scan speed and scan spacing, and an orthogonal experimental approach was applied for training and testing of the system. Verification experiments were utilized to assess the quality of the model and the results showed the high accuracy of ANN for prediction. Vijayaraghavan et al. [15] used a combination of FEM and evolutionary algorithm simulation in order to determine the relationship between inputs (laser power, scan velocity and scan spacing) and the output (density). The results from this work indicated that scan spacing and velocity had the highest impact while scan spacing had the least effect on the density of SLS-fabricated samples. SA algorithm which is part of metaheuristic algorithm is one of the most important and prominent optimizer algorithms which is used frequently in some manufacturing process [16, 13, 17, 18, 19, 20], however there are no previous publications concerning the usage of SA algorithm for the SLS process.

There have been very few publications in regard to usage of GRA for prediction or optimization of laser processes. GRA has however been applied as an optimization technique for many other manufacturing processes [21, 22, 23, 24, 25] The experimental results achieved from the optimal settings predicted from the GRA algorithm show that there is a significant improvement in the related manufacturing process. The benefit of this approach is that the changes in multiple output response can be linked to various input settings which hence streamlines the optimization procedure.

2. Methodology and experimental tools

2.1. Description of ANFIS

For making relationship between input and response parameters adaptive neuro-fuzzy inference system is utilized which is mixture of neural network and fuzzy logic. In this study, the model consists of five layers and each layer includes several nudes. There were fifty sets of parameters studied in the experimental work including forty data points as a training for ANFIS model ten of data points for the model evaluation. For further information about implementation of the ANFIS, interested reader is referred to the following references [15,26].

In this work, in order to make a connection between input parameters and outputs, the ANFIS model was employed. After that, for each outputs, a specific ANFIS model was chosen based on RMSE. For example, because of five inputs, firs layer of ANFIS includes five nudes and the last layer has one nudes which represent of tensile strength.

2.2. Optimization with SA algorithm

One of the most significant algorithms which is broadly utilized for optimization of manufacturing processes is the SA algorithm which is a metaheuristic algorithm and is derived from modeling of thermal annealing. When a metal heated in a high temperature, it will reach to molten point. In this level of temperature, as a result of energy which is given by heating, all of atoms can move easily. When the temperature drops, the atoms will be arranged in the crystalized solid which have low level of energy. Based on the annealing process explanation, SA is an algorithm which is based on accidental exploration which naturally will not be trapped in a specific area, as a result of using the probability distribution function. For further information about implementation of SA, interested reader is referred to the following reference [23].

2.3. Multi response optimization with GRA

GRA is a popular type of optimization method which is used for solving of multi-criteria problems. According to the experimental data, in order to find best optimal condition, tensile strength and elongation should convert to one output. In this analysis, Firstly, data need to be normalized from to zero to one. After that, grey relational coefficient is computed in order to generate a relationship between inputs and responses. Next, in order to find Grey relational grade (GRG), the mean of grey relational coefficient needs to be calculated in relation to outputs. Finally, the result of multiple output process is structured on GRG which is calculated in previous section. This optimization method has been presented in detail previously [23].

3. Material and test specimen

The data examined was recorded in experimental work was performed by Negi et al.[8] and is summarized here for clarity. The materials which are utilized for making parts in SLS process was glass filled polyamide produced by EOS GmbH. This material is including polyamide glass beads and powder. The detailed experimental methodology implemented is indicated in Fig 3.

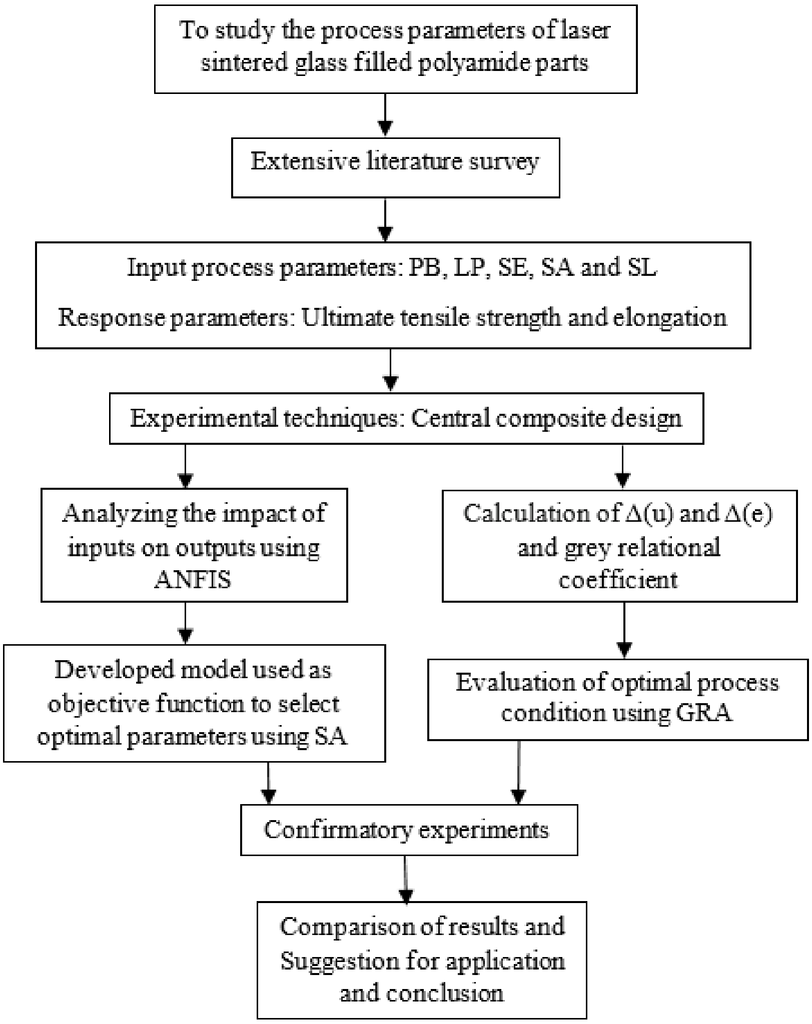

Fig 3. Flow chart of the implemented experimental and modeling methodology.

3.1. Selective laser sintering (SLS) parameters definition

For producing parts in SLS process several input elements are important and if they control sufficiently by the operator, parts will produce better in terms of strength. In this work, the process parameters to fabricate the test specimens are as shown in Table 1. Fig 4 presents the experimentally recorded values of tensile strength and elongation.

Table 1. Process variables and their levels (Negi et al., 2015)

Process parameters	Unit	Symbol	Code levels		
			0	0.5	1
Part bed temperature	ºC	T	176	179	192
Laser power	W	LP	28	32	36
Scan velocity	mm/s	SE	2500	3500	4500
Scan spacing	mm	SA	0.25	0.35	0.45
Scan length	mm	SL	100	120	140

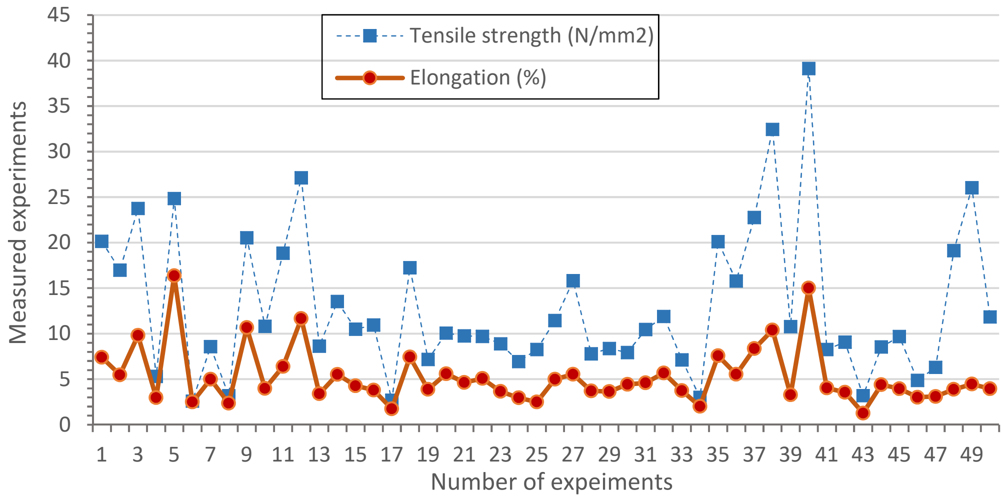

Fig 4. Measured ultimate tensile strength and elongation of the test specimens

4. Results and discussion

Process optimization by ANFIS-SA has two major stages. The initial stage is to determine objective function, and next stage is to mix the objective function and SA for choosing best step setting. The implementation of each step is presented below.

4.1. Development of ANFIS model

For developing the ANFIS model the model needs to be trained. This involves Root Mean Square Error (RMSE) assessment between predicted and actual values after each iteration. Each combination of backward and forward propagations in ANFIS is called an epoch. The model was stopped after the RMSE fell below 0.01 or the number of epoch interactions reached 200. Next, the comparison had been conducted on trial and error results and the model was selected according to precision which is estimated in related to new values in the testing section when they were checked with empirical data. By examining of different structures, ANFIS model for each of two outputs, were selected which was 32 MFs for each input data, which has the minimum of RMSE (Table 2). The basic structure of this model is indicated in Fig 5.

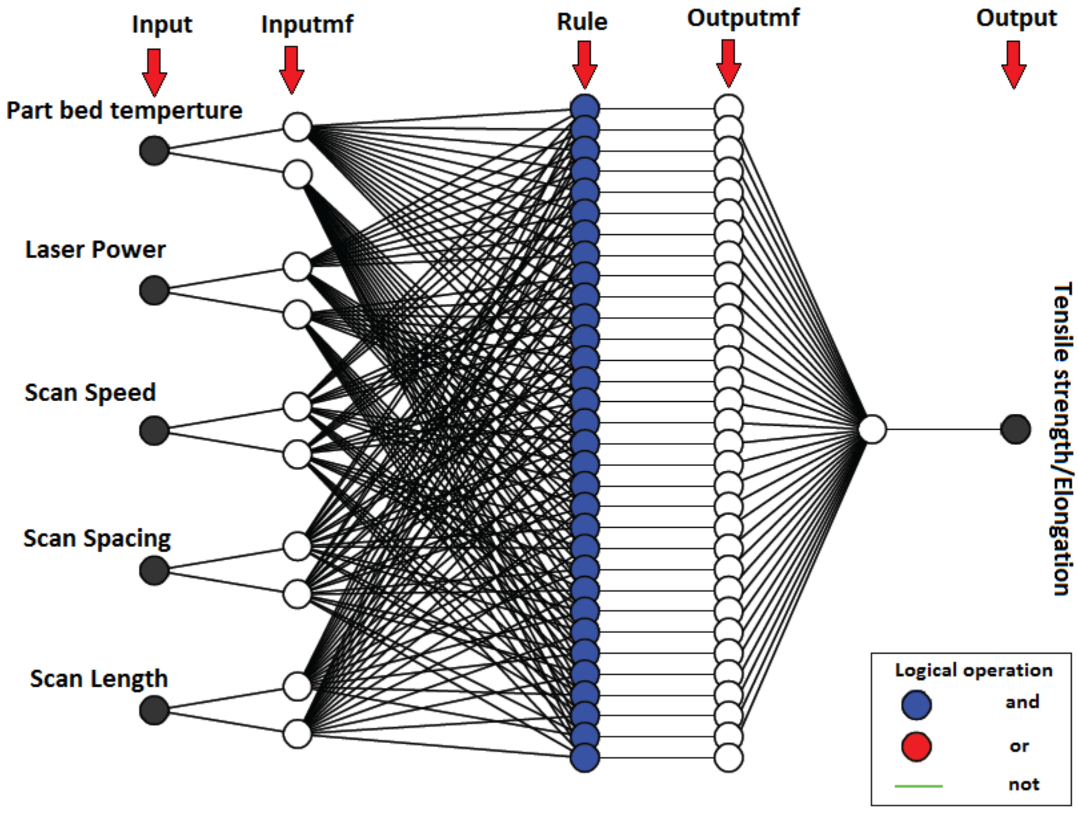

Fig 5. Structure of obtained ANFIS for estimation of ultimate tensile strength and elongation.

Choosing a structure of ANFIS with so many membership functions cause an overfitting and also type of MFs is considered as an essential element for accuracy of the model. In this study, differnet types of MFs namely generalized bell, trapezoid, triangular, Psigmoidal and Gaussian were examined. Table 2 indicates the RMSE of the implemented ANFIS models for tensile strength and elongation. Eight types of membership function were examined and lowest RMSE was selected for each structure model. According to the result of ANFIS model, 2-2-2-2-2 structure with P sigmoidal function had the minimum values of RMSE based on the other MFs and other models for all two outputs. As shown in table 2, P sigmoidal is chosen for both outputs tensile strength and elongation regarding to other types of membership function. Also, Fig 6 and 7 indicates the comparison of measured values through experiments and estimated values with ANFIS for elongation and ultimate tensile strength in 10 experiments out of 50 experiments which are chosen randomly. It can be observed from the figures that there is good confirmation between data which measured experimentally and data which is estimated by ANFIS.

Table 2. Values of RMSE for tensile strength and elongation for various MFs structures.

Membership function	Tensile strength	Elongation
Triangular	19.8556	6.9848
Trapezoid	13.3039	7.0094
Generalized bell	14.2695	6.8417
Gaussian	13.2800	6.8756
Gaussian2	13.2688	9.9613
Pi shaped	13.2834	6.9666
D sigmoidal	13.2480	6.9632
P sigmoidal	**13.2391**	**6.9630**

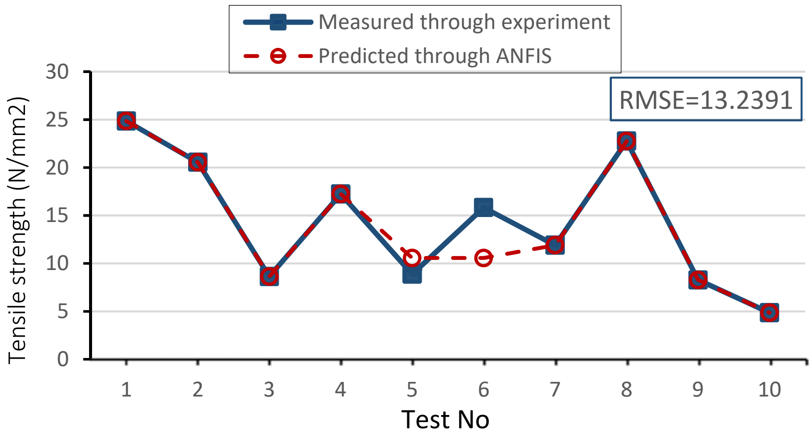

Fig 6. Comparison between measured and estimated data for tensile strength.

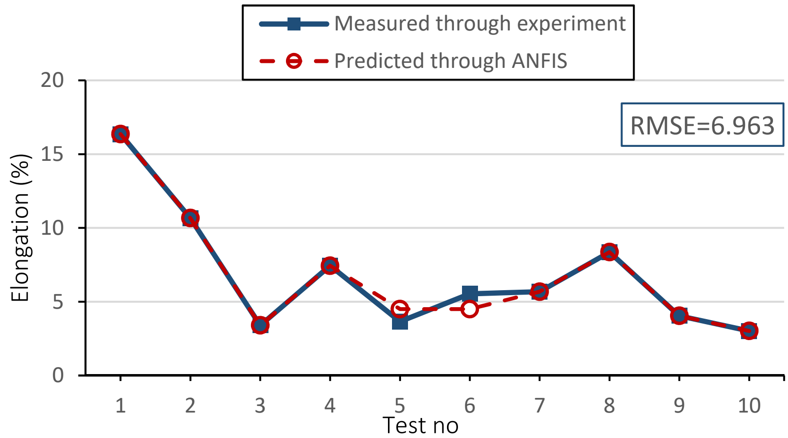

Fig 7. Comparison between measured and estimated data for elongation.

4.2. Analysis of responses: ultimate tensile strength and elongation

Figure 8 depicts the ANFIS response surface for tensile strength. According to RSM model, all of input factors had a significant impact on responses Fig 8(a-c). In particular, tensile strength and elongation were seen to increase with higher laser power (LP), and lower levels of scan speed (SE), and scan length (SL). It would be expected that with these settings, more material will be more melted and therefore greater bonding between the powder materials.

Figs. 8a and 8b show that there is an interaction between the part bed temperature and laser power for ultimate tensile strength and elongation. From the plots, it is evident that the tensile strength and elongation attained maximum values at a high level of part bed temperature (182°C) and at a correspondingly high level of laser power (36 W). These parameters would be expected to result in a higher degree of melting of the polyamide allowing it to flow and adhere better with the glass bead particles and surrounding material. This is beneficial to the densification of the glass-filled polyamide, causing increased relative density of the laser sintered parts. when the density of the part increases, tensile properties will be enhanced. When sintering takes place at a higher level of laser power and part bed temperature, the bond between the powder particles becomes stronger due to better fusion, resulting in increased ductility and strength. On the other hand, when laser power and bed temperature are on lower stage, melting the powder will be impossible due to lower temperature which is transferred to the powder, therefore, resulting lower tensile properties of sintered parts. According to the figure, temperature of part bed has a limitation, but if the temperature is increased distortion in parts will be accrued, resulting in reduced part properties.

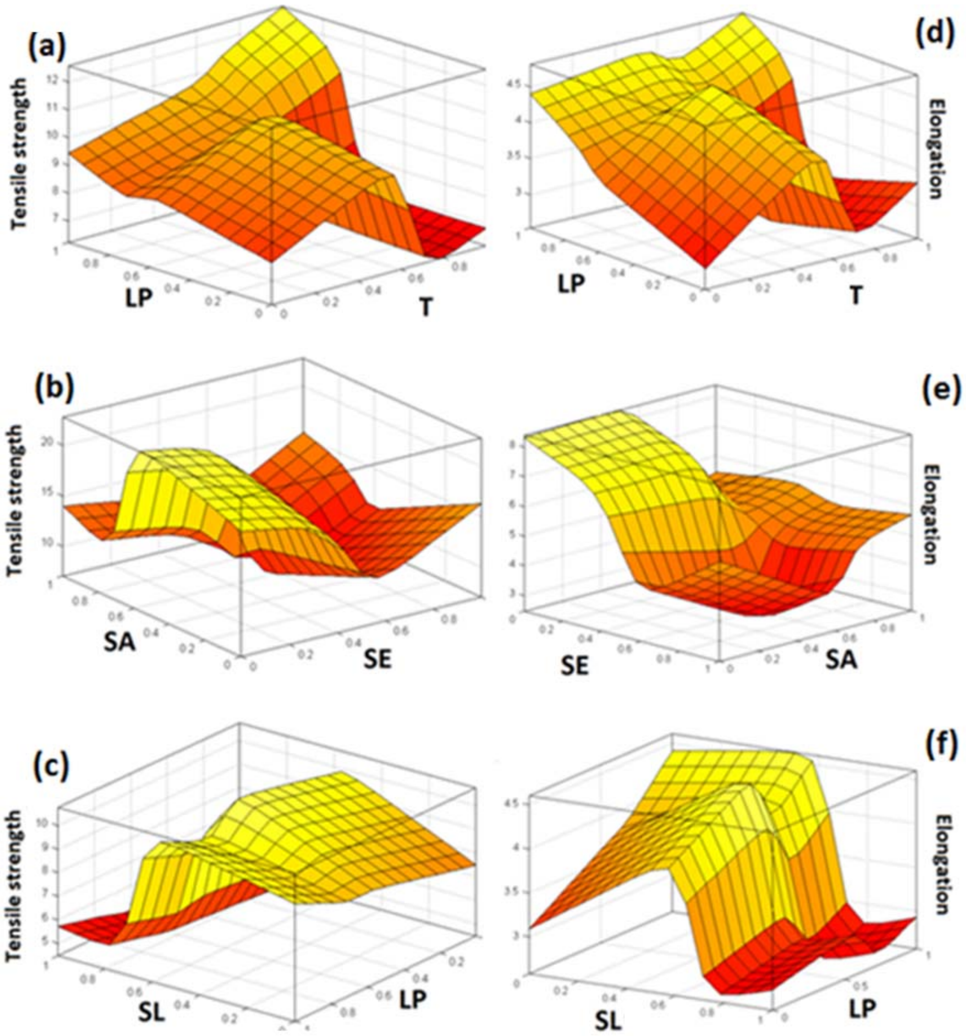

Fig 8. 3D response surface plots of tensile strength and elongation against (a and d) laser power (LP) and part bed temperature (T); (b and e) scan speed (SE) and scan spacing (SA); (c and f) laser power (LP) and scan length (SL).

Figs 8b and 8e demonstrate the interaction effect of scan speed and scan spacing on tensile strength and elongation. From the plots, it can be seen that the tensile strength and elongation attained a maximum value at a low level of scan speed (2500 mm/s) and scan spacing (0.25 mm). This can be described by the phenomenon that all of specimens which are made by SLS process at lower energy density phase (i.e. higher values of scan speed and scan spacing) were less well sintered.

However, very low values of scan speed and scan spacing (which means higher values of energy density) may cause over sintering of powder particles and will result in an unwanted increase in processing time.

Figure 8c and 8f show the interaction effect of laser power and scan length on tensile strength and elongation from which it is observed that the tensile strength and elongation are lowest at the lower value of laser power (28 W) and at the high value of scan length (140 mm). This was due to the lower laser power and longer scan lengths resulting in a lower level of local thermal energy input which was insufficient to completely sinter the powder particles.

4.3. Optimization of SLS process

4.3.1 Optimization of tensile strength and elongation by simulated annealing algorithm

Because of complexity of SLS against variation of input data, choosing of a value in which the procedure maximize tensile strength and elongation is a complex problem. The optimization algorithm techniques can therefore be well applied to provide solutions which can better maximize the mechanical property values from in this process.

In this part, 2-2-2-2-2 ANFIS structure which calculated from last section, will be used as an objective function in order to make maximum values of ultimate tensile strength and elongation. For the optimization algorithm, a MATLAB code was generated with Rastrigin error checking function included. In optimization of the process by ANFIS-SA, the part bed temperature of 180 °C, laser power of 29 W, scan speed 30 mm/s, scan spacing 0.37 m and scan length 133 mm resultant in optimal solution with tensile strength of 34 N/mm^2 and elongation of 11%. Table 3 shows optimal results derived from simulated annealing (SA). According to the optimization these inputs would lead to maximum tensile strength and elongation. For confirmation of the obtained solution from the model, a verification experiment with values from table3 will be performed. If the acquired values of tensile strength and elongation would be seen to be close to those derived from the verification experiment, the modeling and optimization would be considered implemented successfully. Table 4 presents a comparison between the optimal tensile strength experimental results and elongation and the ANFIS model predicted results. It is seen that percentage error is below 5% and 10% for the tensile and elongation values respectively.

Table 3. Optimal proposed parameters and corresponding results obtained through SA.

Process factors					Responses	
Part bed temperature	Laser power	Scan speed	Scan spacing	Scan length	Tensile strength	Elongation
180.19	28.92	3410	0.375	133.564	42.8883	17.383

Table 4. Comparison of tensile strength and elongation of confirmatory experiments with those derived from the developed ANFIS-SA model.

Tensile strength			Elongation		
Measured	Predicted	Error (%)	Measured	Predicted	Error (%)
44.295	42.8883	3.176	15.85	17.383	-9.672

4.3.2 Optimization of process by GRA

As explained in section 3.3 in order to optimize the process by GRA, firstly the experimental results of Figure 4 should be normalized. For this purpose, higher-the-better strategy was used for normalizing of material removal rate and lower-the-better strategy is used for normalizing of both tensile strength and elongation. Then the grey relational coefficients were calculated based on values of normalized data for each response. The coefficients of outputs have been collected to assess GRG that is the overall representative of tensile strength and elongation. In the present work the same weight factors ($W_1=W_2=W_3=0.333$) are considered to construction grey relational grade.

Hence, the hybrid optimization of SLS process has been converted to one equivalent objective function of the process. Figure 9 presents the grey value against the number of experiment for each experimental set of parameters examined.

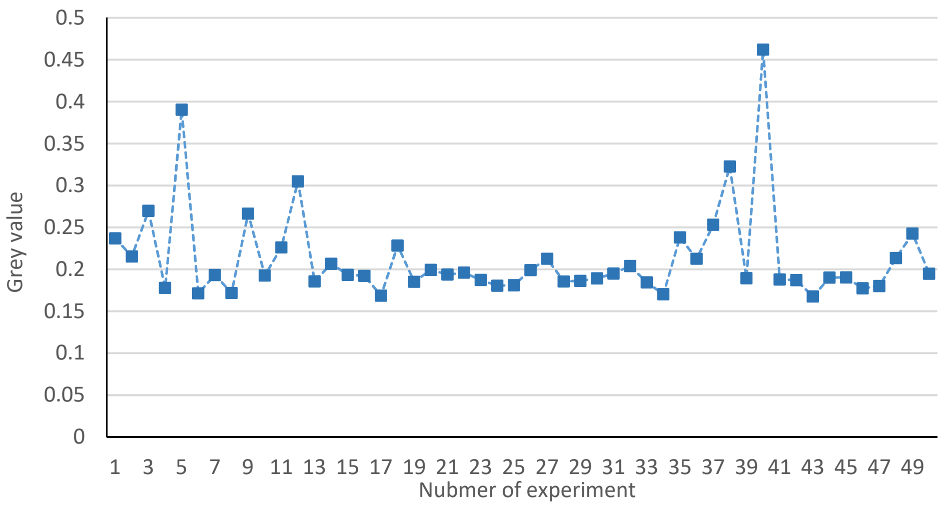

Fig 9. Grey relational value for each experiment run.

Fig.10 presents the main effect plots for the selected processing conditions such as part bed temperature, laser power, scan speed, scan spacing and scan length. The main effect plot provides a representation of the importance of each process elements on the output parameters. In the main effects chart, if the line for a specific process parameter has the biggest slop, then the parameter has the most significant effect, whereas, if the line for a specific element is closest to horizontal line, then that parameter has no significance. Therefore, from the main effects plot scan length and scan speed have slightly more significance than the other inputs on the tensile properties of the glass filled polyamide specimens. From Fig. 10, the optimal parametric combination can be determined. The optimal process parameter setting is 182 ºC (max.), part bed temperature, 28 W laser power (lowest), 2500 mm/s scan speed (lowest), 0.45 mm scan spacing (max.) and 140 mm scan length (max.). Furthermore, the effect of interaction between the two process parameters is shown in Fig. 11. From these plots, it is observed that almost all lines are intersecting with each other; that is, all process parameters have considerable interaction between each other.

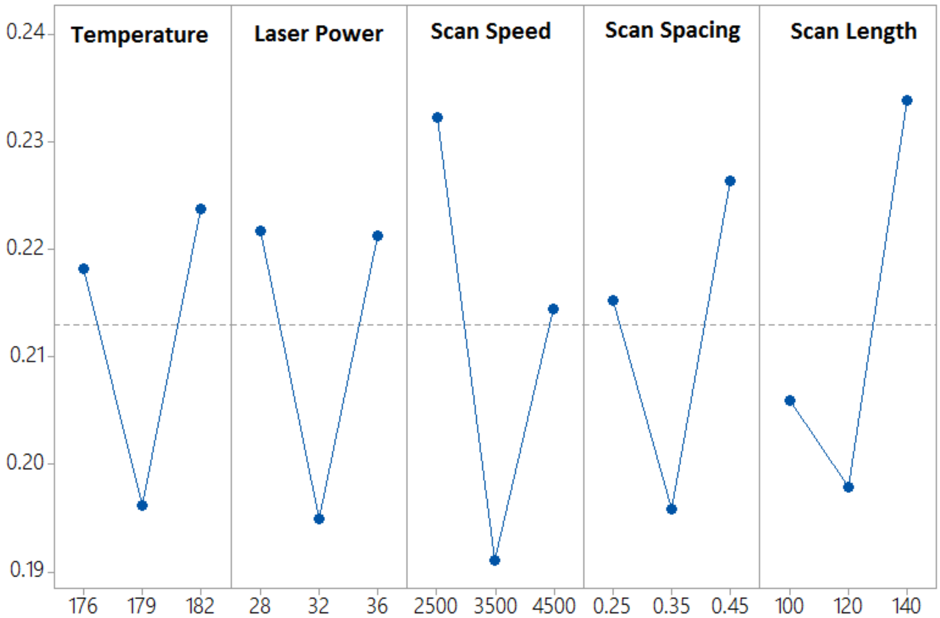

Fig 10. Main effects plot of the grey values for the effects of the input parameters.

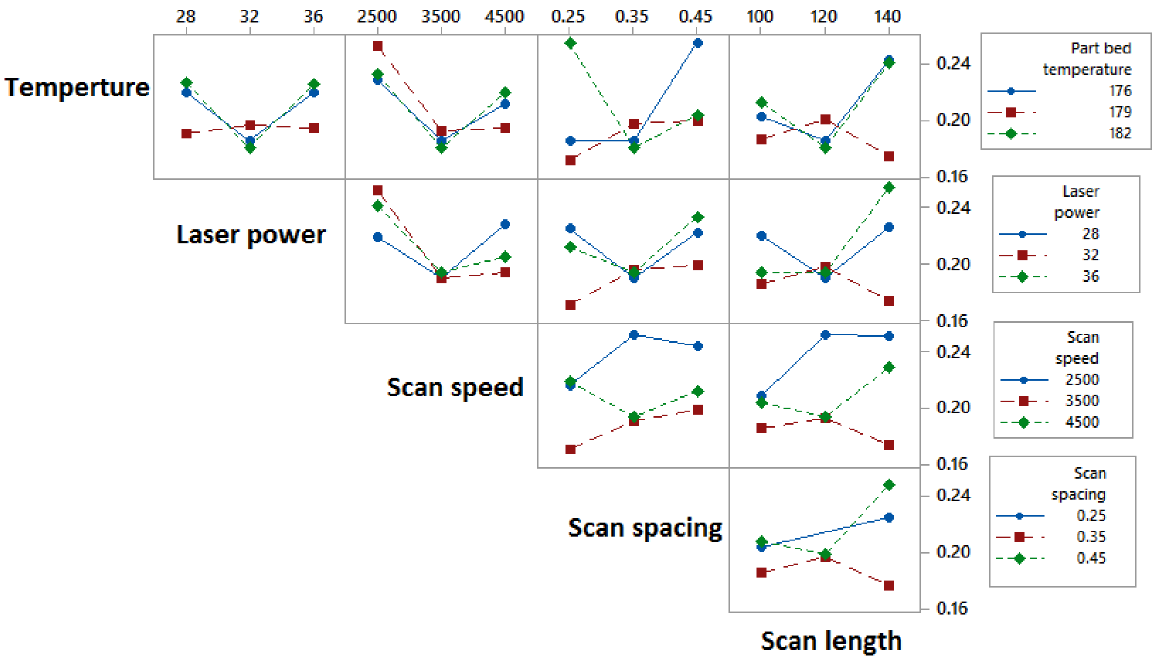

Fig 11. Interaction plot of the determined grey grade values for each of the input parameters.

From Table 5 it is seen that applying a combination of normalized grey relation coefficient of 0.2237 for temperature, 0.2217 for power, 0.2322 for scan speed, 0.2322 for scan spacing, and 0.2338 for scan length resulted in the highest value of GRA and maximum combination of tensile strength and elongation. The levels of the results which result in the maximum tensile strength and elongation correspond exactly with those found from response surface methodology.

Table 5. Response surface for the mean grey relational grade values.

Symbol	Sintering parameters	Level 1	Level 2	Level 3	Max-Min
PB	Part bed temperature	0.2181	0.1961	**0.2237**	0.0056
LP	Laser power	**0.2217**	0.1949	0.2212	0.0276
SE	Scan speed	**0.2322**	0.191	0.2144	0.0412
SA	Scan spacing	0.2152	0.1958	**0.2263**	0.0305
SL	Scan length	0.2059	0.1979	**0.2338**	0.0359
Average grey relational grade=0.2125					

The following step is the verification and prediction of quality characteristics based on the new condition of inputs and outputs which is achieved by GRA. Because of that, experimental verification was performed with the achieved selected input parameters, and tensile strength and elongation. If the GRG results that is acquired from the experiment was close to results from predication, the presented method can be said to be efficient in prediction of optimization process. Table 6 shows the difference between the predicted GRG with the actually acquired from experiments in the selected factor. It can be concluded that there is an acceptable agreement between the results from experiments and GRA. This confirms the function of the suggested method based on the multi objective optimization in manufacturing process needs to optimize the responses as the same time.

Table 6. Results of confirmatory test of the effects of the input factors on the output.

	Initial sintering parameters	Optimal sintering parameters	
		Experiment	Prediction
Setting level	T1, LP1, SE1, SA1, SL1	T3, LP1, SE1, SA3, SL3	T3, LP1, SE1, SA3, SL3
Tensile strength	20.14	31.04	-
Elongation	7.4	9.42	-
Grey relational grey	0.2369	0.2583	0.2765
Improvement of grey relational grade=9.033%			

5. Conclusion

This work is focused on the multi-objective optimization of process elements for the SLS process of glass filled polyamide parts. The main factors examined in this process were part bed temperature, laser power, scan spacing, scan speed and scan length. The main responses were ultimate tensile strength and elongation. For performing of multi-objective optimization two methodologies have been used. The first methodology was based on modeling of tensile strength and elongation by ANFIS and optimization by SA algorithm. The second methodology was based on GRA. After performing optimization of process by these methods, the obtained results were compared together. A summary of achieved results is presented as follows:

An ANFIS based on 2-2-2-2-2-2 structure with Psigmoidal type of MFs led to maximum precision of modeling for tensile strength and elongation by making the minimum values of prediction error. In optimization of the procedure by ANFIS-SA, the part bed temperature of 180 °C, laser power of 29 W, scan speed 30 mm/s, scan spacing 0.37 m and scan length 133 mm resultant in optimal solution with tensile strength of 34 N/mm^2 and elongation of 11%.

The verification experiments were also used to confirm optimal results. The results of validation experiment with GRA and ANFIS-SA approaches are Closely consistent. Due to the ability of ANFIS-SA to search the entire solution space within the process parameter settings examined, ANFIS-SA was seen to outperform the GRA model. This resulted in an increase of the overall tensile strength and elongation results obtained by 14.78 N/mm^2 and 6.4 % respectively for the output of ANFIS-SA compared to GRA. Based on our experiences, we can suggest that ANFIS-

SA be an effective approach to solving a multi-objective optimization problem in manufacturing processes which responses related in a complex manner to the input parameters.

The main reason for the ANFIS-SA model's better result is the searching nature of both ANFIS and SA. With ANFIS and SA, these models consider a continues range for each parameter which leads to an extension of the search space and finding new solutions. While in optimization by GRA, only values which contribute to conducting experiments are considered. Hence, for GRA the searching space is just within the design matrix and it is very small. The ANFIS-SA can be seen in this case to outperform on the basis that it solves the optimization as a continuous problem and it can search all points within the solutions space.

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